BLACK CARBON DYNAMICS: CONCENTRATION, SOURCES, DEPOSITION, AND MODELLING FOR PREDICTION AND POLICY IMPLICATIONS AT AGRA

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Vaishnav Bartaria

Under the Supervision of

Prof. Auroop R. Ganguly
Co-Supervisor
College of Engineering
Northeastern University
Boston, MA, USA

Dr. Ranjit Kumar
Supervisor
Assistant Professor

Department of Chemistry, Faculty of Science
Dayalbagh Educational Institute (Deemed to be University)
Dayalbagh, Agra-282005
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1. INTRODUCTION

Black carbon, also known as soot, is a potent climate-forcing agent that significantly contributes to global warming. It is produced through the incomplete combustion of fossil fuels, biomass, and other organic materials, resulting in a fine black powder that can affect climate and alter surface albedo. Short-lived climate pollutants (SLCPs), such as black carbon (days), tropospheric ozone (weeks), methane (12 years), and hydrofluorocarbons (15 years), not only contribute to climate change but also pose severe health risks and environmental damage. Reducing black carbon can yield immediate climate benefits, offering a quicker impact compared to longer-term CO_2 mitigation efforts. Black Carbon (BC), a short-lived climate forcer, is an important constituent of fine particulate matter ($PM_{2.5}$), but its measurement is cumbersome, and its impacts are monstrous. Hence, it has attracted the attention of the scientific community worldwide; however, studies on the identification of emission sources and the transfer of BC from the atmosphere to the Earth's surface are rare and sporadic. The prediction of BC and scaling up in data-poor regions are crucial to safeguarding humankind from the threat of black carbon, particularly in the context of global warming, climate change, and deteriorating air quality. Artificial Intelligence (AI), Machine Learning (ML), and Soft Computing can play a significant role in mitigating the menace of black carbon.

The term "black carbon" was introduced by physicist Tihomir Novakov in the 1970s. Michael Faraday first identified soot, which includes black carbon, as carbon from incomplete combustion of fuels. Black carbon (BC) is a pure carbon component of fine particulate matter (PM $\leq$ 2.5 μm). It is a major particle in both anthropogenic and natural soot. BC is a component of fine particulate matter from incomplete combustion, with a graphite-like structure. Composed of over 60% carbon and elements like hydrogen, oxygen, nitrogen, and sulphur, BC arises from sources such as power plants, vehicles, wildfires, and biomass burning (Ramanathan & Carmichael, 2008). It affects climate in several ways: by absorbing solar radiation and warming the atmosphere, reducing snow and ice albedo when deposited, and influencing cloud properties and their impacts on climate. BC has health implications also. BC causes human morbidity and premature mortality (Janssen et al., 2012; Gupta et al., 2023).

BC warms the Earth by absorbing sunlight and heating the atmosphere, and it also reduces the Earth's albedo (reflectivity) when deposited on snow and ice. This leads to an increase in global temperatures, making black carbon a significant contributor to climate change. BC is the most potent climate forcing agent with a radiative forcing (RF) estimate of +1.1 (+0.17 to +2.1) W m^{-2}, which is ~ 65% of that of CO_2 (Bond et al., 2013). BC is recognized as the second most significant climate forcer after carbon dioxide (CO_2). Unlike long-lived greenhouse gases like carbon dioxide (CO_2), which remain in the atmosphere for over 100 years, BC stays in the atmosphere for only several days to weeks, making its reduction a powerful short-term climate mitigation strategy. It is a form of pure carbon and a critical component in the global climate system.

BC particles are highly effective at absorbing sunlight due to their high mass absorption cross-section (MAC) of over 5 $m^2 g^{-1}$ at 550 nm, with the highest absorption typically occurring in the visible to near-infrared range, from approximately 600 to 950 nm. The MAC of black carbon can reach values up to 10 - 12 $m^2 g^{-1}$ within this range (Knox et al., 2009; Drinovec et al., 2015). They are refractory, with a volatilization temperature around 4000 K, and insoluble in water and organic solvents (Bond et al., 2006). Composed of small carbon spherules (10-50 nm) that aggregate into larger clusters, BC has a high proportion of graphite-like sp^2-bonded carbon atoms. These properties enable BC to significantly impact atmospheric warming, cloud formation, weather patterns, and the Earth's radiative balance (Drinovec et al., 2015).

Exposure to black carbon has been linked to a range of health problems, including respiratory issues, cardiovascular diseases, and even cancer. The World Health Organization (WHO) has identified BC as a component of fine particulate matter ($PM_{2.5}$) that can penetrate deep into the lungs, causing inflammation and damage to lung tissue (Janssen et al., 2012; Yang et al., 2021; Song et al., 2022). Respiratory diseases, such as asthma and bronchitis, are exacerbated by BC particles, which are tiny enough to penetrate deep into the lungs, leading to increased symptoms and hospital admissions for these conditions. Moreover, exposure to BC affects not only the lungs but also the heart, leading to increased rates of heart attacks, strokes, and other cardiovascular diseases (Lequy et al., 2021; Wang et al., 2021). These tiny particles can cause inflammation and stress on the heart, leading to long-term health issues. For those with pre-existing health issues, BC can make things worse, particularly for the

elderly, children, and those with chronic health conditions, making them more susceptible to their environment's harmful effects. Additionally, exposure to BC has been linked to neurological effects, such as cognitive impairment and neurodegenerative diseases. The International Agency for Research on Cancer (IARC) has classified BC as a possible carcinogen to humans (Morfeld & McCunney, 2011). Understanding these health impacts is crucial for protecting urban and rural populations from the dangers of air pollution. Hence, reducing exposure to BC is essential for mitigating these health risks and promoting a healthier environment for all.

1.1 Origin of Black Carbon

BC gets generated when carbon-based fuels are combusted without enough oxygen. This process occurs due to incomplete combustion, where the carbon in the fuel is not fully oxidized. Even when there is a sufficient oxygen supply, the inefficient mixing of reactants can result in fuel-rich, oxygen-poor zones, leading to localized incomplete combustion. In these zones, carbon does not completely convert to carbon dioxide, resulting in the formation of BC. Polycyclic aromatic hydrocarbon (PAH) molecules undergo a complex sequence of chemical transformations to produce precursors of BC. Initially, these PAH molecules coagulate to form particle nuclei, which then expand by surface processes such as condensation and aggregation. The resulting black carbon spherules are distinctively different from other atmospheric particles (Grisdale, 1953). Electron microscope photos reveal that these spherules have wrinkled graphitelayers, which create a shell surrounding a hollow or disordered interior (Heidenreich et al., 1968). These structures are a key identifier of black carbon particles. Nanoparticles of black carbon exhibit high carbon-to-hydrogen ratios, typically in the range of tens of nanometers in size (Martins et al., 1998; Pósfai et al., 1999; Li et al., 2005). These small, graphitic spherules tend to accumulate and form larger aggregates. After their production, these graphitic spherules aggregate to form clusters or fractal chain-like formations, which consist of hundreds or even thousands of individual spherules (Medalia and Heckman, 1969; Li et al., 2005). The fractal nature of these aggregates increases their surface area, which plays a significant role in their interactions with atmospheric components and their overall environmental impact. The fate of black carbon particles is determined by the conditions within the combustion process. Keeping the combustion exhaust hot and mixing it with enough oxygen can eliminate carbon particles from the

combustion chamber through oxidation reactions (Lee et al., 1962). This process can reduce the amount of black carbon emitted into the atmosphere. However, if these conditions are not met, the black carbon particles are expelled into the atmosphere, contributing to air pollution and climate change. Understanding the formation, structure, and evolution of black carbon is crucial for addressing its environmental and health impacts.

1.2 Sources of Black Carbon

Black carbon (BC) may get originated from a variety of sources, including fossil fuel combustion, biomass burning, industrial processes, and natural sources. Fossil fuel combustion is a major source of BC, particularly from diesel engines, coal combustion, and biomass burning. Coal combustion for electricity generation and industrial processes is another major source of BC. Biomass burning, including wildfires, agricultural burning, and domestic biomass burning, also contributes to BC emissions. Biomass burning is a significant source of BC, particularly from wildfires, agricultural burning, and domestic biomass burning. Wildfires, especially in tropical regions, can emit large amounts of BC. Agricultural burning, such as crop residue burning, is another significant source of black carbon. The Haryana and Punjab regions of the Indo-Gangetic Basin (IGB) are well-known for stubble burning, which impacts the air quality of the entire IGB region, particularly during the post-monsoon season (Gupta et al., 2017). Domestic biomass burning for cooking and heating is also a significant source of BC, particularly in developing countries and rural areas. Industrial processes, such as cement production, steel production, and waste incineration, are also significant sources of BC. Cement production is a significant source of BC, particularly due to the use of fossil fuels and biomass. Steel production is another industrial process that emits BC. Waste incineration, including municipal solid waste and hazardous waste, can also emit BC. All these sources can be grouped as anthropogenic sources of BC.

Natural sources of BC include volcanic eruptions and dust storms. Volcanic eruptions can emit large amounts of BC into the atmosphere. Dust storms, particularly in arid regions, canalso contribute to BC emission. They are primarily produced by anthropogenic causes, but they can also result from natural wildfires (Bond et al., 2004). These sources vary widely in their contribution to global BC emissions, with residential biomass burning being the dominant source in many developing regions, while

transportation and industrial sources are more significant in developed countries. Two approaches have been used to obtain information on the sources of BC: (i) in-situ measurements combined with source apportionment methods that are scaled up to regional or global levels (Johnson et al., 2013; Briggs and Long, 2016); and (ii) bottom-up models based on emission inventories, including data relating to fuel consumption and land use (Chow et al., 2010; Bond et al., 2013), which can be used to model past and future concentrations (Wang et al., 2014; Liousse et al., 2014).

There are seven hotspots of black carbon emissions such as eastern China, northern India, Europe, North America, Africa, Asia, and the tropics. These regions account for a significant portion of global black carbon emissions (Bond et al., 2013). Asia, particularly South and Southeast Asia, is a major hotspot for black carbon emissions. In this region,emissions are driven by a combination of residential biomass burning, brick kilns, and agricultural residue burning. Africa is another significant emitter, primarily due to widespread biomass burning. In contrast, North America and Europe contribute to black carbon emissions largely through transportation and industrial activities, though their overall contributions are smaller compared to developing regions due to stricter emission controls.

In north India, the Indo-Gangetic Basin (IGB) is a major black carbon (BC) hotspot due to its high population, agricultural activities, and reliance on biomass for cooking. Emissions peak in winter from biomass burning and diesel engines (Gupta et al., 2017). Key sources include agricultural burning in Punjab and Haryana and vehicular emissions in cities like Delhi. The region's geography and weather conditions worsen BC accumulation, leading to severe air quality issues and contributing to glacier melt in the Himalayas. Understanding these emission patterns is crucial for estimation of transfer from atmosphere to earth surface (deposition) and effective mitigation.

1.3 Deposition of Black Carbon

Once black carbon (BC) is emitted from various sources, it travels from one location to another, influenced by wind speed and wind direction, interacts with other pollutants in the atmosphere, and finally gets deposited from the atmosphere to the underlying earth surfaces. Deposition is the process by which atmospheric black carbon (BC) is transferred to the Earth's surface, playing a crucial role in removing pollutants from the atmosphere. This process occurs through two main mechanisms: wet deposition and dry deposition. Wet deposition involves the transfer of BC through precipitation,

where BC particles act as cloud condensation nuclei(CCN) and are incorporated into rain or snow, ultimately reaching the surface. Despite BC's hydrophobic nature, studies like Budhavant et al. (2019) have detected BC in rainwater,highlighting the complexity of wet scavenging. Dry deposition, on the other hand, is particularly important in regions like India, where dry conditions prevail throughout much of the year. This process involves the direct transport and accumulation of BC particles onto surfaces during periods without precipitation. The rate of dry deposition depends on the particle size, as well as the physical and chemical characteristics of the particles produced at combustion sources and the nature of the underlying surfaces. Dry deposition of BC has significant environmental impacts, such as darkening snow and ice surfaces, which accelerates glacier melting by reducing surface albedo, and affecting plant photosynthesis by settling on leaf surfaces (Hicks, 1986; Kumar et al., 2003). The dry deposition flux (F) of black carbon can be calculated using the formula:

$$F = Vd \times C$$

Where, Vd is the deposition velocity, and C is the concentration of BC at a reference height. The deposition velocity (Vd) is further defined by the formula (Hicks, 1986; Gupta, 2021):

$$Vd = 1/\mathrm{R}\ (Ra+Rb+Rc)$$

Where R_a is the aerodynamic resistance, R_b is the quasilaminar resistance, and R_c is the surface resistance. Dry deposition is critical in regions with high snow and ice cover, like the Himalayas, where BC deposition accelerates snowmelt by affecting the snowpack's reflective capacity (Hansen & Nazarenko, 2004; Menon et al., 2010; Yasunari et al., 2013). The dry deposition flux of BC affects various ecosystems, including lakes, marine sediments, vegetation, foliar surfaces, and materials across the globe (Kumar et al., 2003; Bergin et al., 2014). While several techniques have been used to measure dry deposition (Yamaguchi et al., 2012; Yasunari et al., 2013) studies specific to India are limited, particularly for black carbon.

1.4 Effects of Black Carbon

Black carbon particles reaching the ground surface have a greater or lesser impact onthe underlying surfaces, depending on the flux of dry deposition and their total input through both dry and wet deposition processes. BC, a potent climate-forcing agent, has far-reaching consequences for the

environment, human health, and the economy. Its effects are multifaceted and can be broadly categorized into direct, indirect, semi-direct impacts, and long-term effects.

1.4.1 Direct Effects of Black Carbon

(i) Climate Change

Black carbon (BC) is a powerful climate forcer due to its intense ability to absorb solar radiation. When present in the atmosphere, BC particles absorb sunlight and convert it into heat, leading to an increase in atmospheric temperatures and disrupting the Earth's radiative balance. This contributes significantly to global warming, particularly in regions with high BC emissions. Although BC has a short atmospheric lifetime (days to weeks), its warming effect is much stronger (per unit mass) compared to other climate pollutants, making it a crucial factor in near-term climate change (Zhang et al., 2011; Bond et al., 2013; Schuur et al., 2014).

(ii) Snow/Ice Albedo Effect

The albedo effect measures a surface's reflectivity, with snow and ice reflecting most incoming solar radiation. When black carbon settles on these surfaces, it darkens them, reducing their albedo and causing increased solar absorption. This leads to higher surface temperatures and accelerates the melting of snow and ice. This effect is especially alarming in polar and high-altitude regions, where it hastens glacier and ice sheet loss, contributing to global sea-level rise and threatening ecosystems (Flanner et al., 2007; Yasunari et al.,2013; Gul et al., 2024).

(iii)Human Health

Black carbon particles are a major component of fine particulate matter ($PM_{2.5}$), which can be inhaled deeply into the lungs. Exposure to black carbon is associated with a range of adverse health effects, particularly respiratory and cardiovascular problems (Janssen et al, 2012). The tiny particles can penetrate the respiratory system, leading to inflammation, exacerbation of asthma, reduced lung function, and increased risk of lung cancer. Chronic exposure to high levels of black carbon is also linked to heart attacks, strokes, and premature death. Vulnerable populations, including children, the elderly, and those with pre-existinghealth conditions, are particularly at risk. Moreover, black carbon's role in reducing air quality contributes to broader public health challenges, especially in urban areas with heavy traffic and industrial activities (Yang et al., 2021; Song et al., 2022; Gupta et al., 2023).

(iv) Regional Climate Effects

Black carbon can cause regional variations in temperature and precipitation. Its presence in the atmosphere can lead to a reduction in surface temperature in regions where the particles block sunlight from reaching the ground, a phenomenon known as the "dimming effect (Ramanathan et al., 2005)." This effect can disrupt local weather patterns, influencing everything from temperature to rainfall distribution (precipitation), potentially leading to droughts or altered growing seasons for agriculture (Zhang et al., 2011; Bond et al., 2013; Schuur et al., 2014).

1.4.2 Indirect Effects of Black Carbon

(i) Cloud Formation

Black carbon influences cloud formation by acting as cloud condensation nuclei (CCN), affecting cloud droplet size and number (Novakov & Penner, 1993; Koch & Genio, 2010). This alters cloud reflectivity and lifetime, impacting precipitation and Earth's energy balance. Additionally, black carbon can suppress cloud formation by absorbing solar radiation, heating the air, and reducing humidity, which decreases cloud cover and amplifies warming (Koch & Genio, 2010).

(ii) Agriculture

Black carbon deposition on plants can hinder photosynthesis by blocking sunlight, leading to reduced crop yields. It also alters the microclimate and can change soil chemistry, affecting plant growth and soil health. In regions dependent on agriculture, this poses a risk to food security and livelihoods (Chung et al., 2012; Sharma et al., 2012; Kharol et al., 2012).

(iii) Precipitation

Black carbon impacts precipitation by altering cloud properties, which can either enhance or suppress rainfall depending on the region (Menon et al., 2002; Wang, 2007). These changes can disrupt regional weather patterns, potentially leading to shifts in monsoons, droughts, or floods, affecting water resources, agriculture, and ecosystems, especially in areas sensitive to climate variability (Bond et al., 2013; Wu et al., 2018).

(iv) Material

Black carbon damages building materials and cultural heritage sites by depositing on surfaces,

causing discoloration, staining, and material deterioration. This is especially harmful to historic buildings and monuments, where it accelerates degradation, leading to costly restoration and risking the loss of cultural heritage (Bergin et al., 2014; Banerjee et al., 2024).

(v) Ocean Circulation and Marine Ecosystems

Black carbon deposition on the ocean surface alters thermal properties, affecting ocean circulation and nutrient distribution which is crucial for marine life, especially phytoplankton (Budhavant et al., 2019). This can impact sea surface temperatures and influence weather patterns like monsoons, with broad ecological and climatic consequences (Ren et al., 2022).

(vi) Ecosystem Disruption

Black carbon disrupts ecosystems by altering habitats. In Polar Regions, it accelerates sea ice loss, threatening species like polar bears and seals. In forests, it affects soil chemistry and plant growth, leading to shifts in species composition and ecosystem dynamics (Lian & Xing, 2017; Menon et al., 2010).

1.4.3 Semi-Direct Effects of Black Carbon

(i) Atmospheric Heating

The semi-direct effect of black carbon involves its absorption of solar radiation, causing localized heating in the atmosphere. This warming can alter atmospheric stability and circulation, impacting regional weather and climate (Koch & Genio, 2010). Additionally, it enhances the greenhouse effect by trapping longer wave radiation, creating a feedback loop that exacerbates global warming (Bond et al., 2013; Schuur et al., 2014).

(ii) Glacier Melting

Black carbon on glaciers accelerates melting through both albedo reduction and atmospheric heating. This increases surface temperatures, speeding up glacier melt, especially in regions like the Himalayas (Santra et al., 2019). Accelerated glacier melting can alter river flow, water availability, and seasonal patterns, impacting water resources, agriculture, and ecosystems downstream (Menon et al., 2010; Lian & Xing, 2017; Wu et al., 2018).

(iii) Regional Circulation

Black carbon alters regional circulation patterns by modifying temperature gradients and atmospheric stability. Its heating effect can strengthen or weaken systems like monsoons and jet streams, affecting weather patterns, precipitation, and extreme events. This can lead to localized heat islands, impacting regional climate and weather (Wang, 2007; Chung et al., 2012;Sharma et al., 2012; Ren et al., 2022).

(iv)Feedback Loops in the Climate System

Black carbon drives climate feedback loops by amplifying warming. Its warming effect can release methane from permafrost, a potent greenhouse gas, intensifying global warming. Additionally, black carbon reduces ice reflectivity, increasing heat absorption and accelerating ice melt, which further raises temperatures (Schuur et al., 2014; Wu et al., 2018; Santra et al., 2019).

(v) Impacts on Atmospheric Composition

Black carbon interacts with pollutants like sulphur dioxide, enhancing the formation of secondary pollutants such as ozone and particulate sulphate (Liu et al., 2015). This interaction worsens air quality and its impacts on health and the environment. Additionally, black carbon can alter the oxidative capacity of the atmosphere, affecting the lifecycle of climate-relevant gases like methane (Koch & Genio, 2010; Smith et al., 2020).

1.4.4 Long-Term Effects of Black Carbon

(i) Global Warming Potential

Although black carbon remains in the atmosphere for a shorter period compared to greenhouse gases like CO_2, its global warming potential during that time is significantly higher (Kirchstetter et al., 2004; Moteki et al., 2010). Efforts to reduce black carbon emissions can therefore have immediate benefits in slowing the rate of climate change, making it a key target for short-term climate mitigation strategies.

(ii) Impact on Policy and Regulation

The understanding of black carbon's effects has led to policy initiatives aimed at reducing emissions. However, the complexity of its interactions with other atmospheric components means that policies must be carefully designed to avoid unintended consequences, such as increases in other types of pollutants. International cooperation is crucial, as black carbon can be transported across borders, affecting regions far from its source (Ramanathan & Carmichael, 2008).

The study of black carbon is crucial due to its significant contribution to global warming, with a global warming potential 460-1,500 times higher than CO_2 over a 100-year time frame (National Oceanic and Atmospheric Administration). In fact, black carbon is responsible for 18% of the warming attributable to all greenhouse gases on a global scale (Hansen et al., 2000). As the second strongest contributor to current global warming after carbon dioxide emissions (Ramanathan & Carmichael, 2008), reducing black carbon emissions can significantly slow global warming, improve air quality, and protect human health (WorldHealth Organization, 2012). Black carbon emissions are expected to increase by 25% by 2030, highlighting the urgent need for action (United Nations Environment Programme, 2011). Recognizing this, research initiatives should be launched to address the knowledge gaps in black carbon's source apportionment, dry deposition flux, and high-resolution modelling. The Indian Ocean Experiment (INDOEX) intensive field phase was conducted from January through March 1999 over the tropical Indian Ocean. Notable among these efforts is the ISRO- GBP SALC project (2004-05), followed by the Indo-US Experiment Project for Aerosol Research. More recently, the ISRO GBP ARFI project (2022-24) has continued to explore blackcarbon's role in climate change.

The pressing issue of black carbon (BC) emissions poses a critical challenge, with wide-ranging impacts on the environment, human health, and the economy. Addressing these challenges requires a comprehensive and innovative approach, which is the focus of the proposed study titled "Black carbon dynamics: concentration, sources, deposition, and modelling for prediction and policy implications at Agra." This research aims to fill significant knowledge gaps, particularly in under-researched suburban regions, on the dynamics of BC using advanced scientific approaches such as the optical attenuation method, radiocarbon tracer technique, artificial intelligence (AI), machine learning (ML), and satellite imagery. The study's primary goal is to develop a nuanced understanding of BC concentrations, source interpretation, deposition patterns, prediction and ultimately providing robust data to inform society for their safeguard, effective control measures and policy strategies.

2 REVIEW OF LITERATURE

Black carbon (BC) is a significant atmospheric pollutant, known to exert a strong influence on radiative forcing, climate change, and public health. Several studies have investigated BC's concentration, sources, and radiative forcing. Additionally, depositional studies have explored BC's

impact on snow and ice albedo, while recent research has also employed machine learning models to predict BC concentrations and sources. Although black carbon (BC) has been studied globally, with numerous investigations on its concentration, radiative forcing, etc., a limited and sporadic study is available on source interpretation, depositional impacts, and predictive modeling.

International

Black carbon (BC) measurement is a crucial aspect of understanding its impact on climate and air quality. One of the most widely used instruments for measuring BC is the aethalometer, which was first developed by Hansen et al. (1984). The Aethalometer measures the absorption of light by aerosols, which is directly proportional to the BC concentration. This instrument has been widely used in various studies to measure BC concentrations in different environments, including urban and rural areas (Hansen et al., 2000; Chow et al., 2004). The Single Particle Soot Photometer (SP2) has been shown to provide high-precision measurements of BC concentrations and has been used in various field campaigns and laboratory studies. Other studies have also explored the use of alternative techniques, such as the Multi-Angle Absorption Photometer (MAAP) and the Particle Soot Absorption Photometer (PSAP), which have been shown to provide accurate measurements of BC concentrations (Petzold et al., 2005; Virkkula et al., 2007). Another important study on BC measurement techniques is the use of the SP2, which measures the scattering and absorption of light by individual particles (Moteki et al., 2010). These studies have contributed significantly to our understanding of BC measurement techniques and have paved the way for further research in this area. Akagi et al. (2011) employed an OC-EC analyzer to investigate BC emissions from biomass burning in Africa. The study found that BC emissions from biomass burning were significantly higher than previously estimated, contributing to regional climate change. Kirchstetter et al. (2004) utilized an OC-EC analyzer to measure black carbon (BC) concentrations in $PM_{2.5}$ samples from various locations worldwide, including the United States, Europe, and Asia. The results showed a strong correlation between BC and elemental carbon (EC) concentrations, highlighting the importance of BC in climate forcing. Ceolato et al. (2022) introduced a novel remote sensing technique using the Colibri instrument and Picosecond Short-Range Elastic Backscatter Lidar (PSR-EBL) to measure black carbon aerosol number and mass concentration with high precision. By applying a forward inversion method and

radiometric calibration based on the Rayleigh–Debye–Gans for Fractal-Aggregates (RDG-FA) theory, the technique successfully quantifies aerosol properties at short distances (centimeter range resolution) and rapid intervals (millisecond time resolution) using a Jet A-1 kerosene pool fire as a test case.

BC concentrations show significant global variability, with the highest recorded levelof 21.7 μg m^{-3} in Lahore, Pakistan, during winter 2005-2006 (Husain et al., 2007), and the lowest in Minicoy, India, ranging from 0.065 to 0.22 μg m^{-3} (Beegum et al., 2008). In the Tibetan Plateau, BC levels varied between 2.25 μg m^{-3} and 8.74 μg m^{-3} at Qiyi and Zhadang, respectively (Ming et al., 2008). Black carbon levels in urban areas of Europe and Asia have been reported as moderate, with concentrations of 1.66 μg m^{-3} in Zurich (Putaud et al., 2004) and 5.7 μg m^{-3} in Tokyo (Kondo et al., 2007). These differences highlight the influence of regional sources and the need for targeted pollution control strategies. Black carbon (BC) concentration exhibits significant variability across temporal scales, influenced by human activities and meteorological conditions. Studies have shown that BC levels follow distinct diurnal patterns, typically peaking during morning and evening rush hours, driven by vehicular emissions and reduced boundary layer heights. In urban areas like Los Angeles (Kim et al., 2018) and Beijing (Cao et al., 2013), BC concentration increases during the morning due to heavy traffic and atmospheric inversion. In addition, Zhang et al. (2009) observed that BC concentrations in Mexico City were influenced by traffic emissions and nocturnal boundary layer formation. Seasonally, BC concentration tends to be higher in winter than in summer, largely due to increased biomass burning, residential heating, and unfavorable meteorological conditions such as lower boundary layers and stagnant air masses. For instance, studies from Northern India (Latha & Badarinath, 2005) and China (Cao et al., 2013) report elevated BC levels during winter months. Similarly, in Europe, Reche et al. (2011) observed wintertime peaksin BC concentrations attributed to residential heating and lower atmospheric mixing. In North America, BC concentrations tend to follow similar seasonal trends, with higher levels during colder months. Wang et al. (2014) showed that BC concentrations in urban areas like Boston peaked during winter due to residential heating, while summer levels were lower due to stronger atmospheric dispersion. Likewise, Schwarz et al., 2010 observed that the Arctic has seen reductions in BC levels during the summer months, but winter concentrations remain elevated, largely

due to long-range transport from Eurasian regions, where winter heating is prevalent. Long-term trends in BC concentrations reflect broader emissions and policy interventions. Over the past decade, developed regions such as Europe and North America have shown a declining trend in BC levels, thanks to regulatory measures and advancements in emission control technologies (Wang et al., 2016). For instance, in Los Angeles, Kim et al. (2018) documented a decline in BC levels between 1999 and 2015, largely due to stringent vehicle emissions standards. Similarly, in Europe, long-term studies report decreasing BCtrends due to policies aimed at reducing traffic and industrial emissions (Reche et al., 2011). In contrast, developing regions like Southeast Asia and Africa have experienced rising BC concentrations due to industrialization, urbanization, and the continued reliance on biomass fuels for energy (Liousse et al., 2014). Zhang et al. (2009) documented rising BC levels in the Indo-Gangetic Plain and Eastern China due to agricultural residue burning, industrial activities, and population density. The role of open biomass burning in the Amazon Basin and sub-Saharan Africa has also been significant in elevating BC levels during the dry season (Gustafsson et al., 2009; Liousse et al., 2014). Globally, hotspots of BC emissions, including regions such as the Indo-Gangetic Plain, Eastern China, and sub-Saharan Africa, continue to experience some of the highest BC concentrations. The Indo-Gangetic Plain is especially affected by seasonal agricultural burning, particularly post-monsoon (Sharma et al., 2017). Additionally, BC concentrations in sub-Saharan Africa remain high year-round due to persistentbiomass burning (Venkataraman et al., 2005). The persistence of high BC levels is also attributed to local meteorological conditions, such as thermal inversions, which trap pollutants close to the surface during the winter season.

The identification of black carbon (BC) sources relies on a combination of observational techniques and modelling approaches. The Aethalometer, which measures BC concentrations at multiple wavelengths, helps distinguish between biomass burning and fossil fuel combustion sources (Sandradewi et al., 2008; Snyder & Schauer, 2007). Modelling approaches like Positive Matrix Factorization (PMF) (Reff et al., 2007) and Weather Research and Forecasting model coupled with chemistry (WRF-Chem) (Grell et al., 2005; Zhang et al., 2015) are used to resolve BC sources from ambient measurements and simulate BC transport and deposition on regional scales. The Aethalometer-based method of using multiple wavelengths, particularly the 370 nm and 880 nm

channels, has been extensively applied in several international studies to differentiate between black carbon (BC) sources. Sandradewi et al., 2008, in Switzerland, observed a clear separation between biomass burning and traffic-related BC, with higher Abs (370nm) / Abs (880nm) ratios linked to increased biomass burning during winter heating periods. Their study demonstrated that wood combustion was the predominant source of BC in rural regions during colder months. Similarly, Zotter et al. (2017) applied the two-wavelength Aethalometer method across several European sites and concluded that BC from biomass burning contributes significantly to wintertime aerosol concentrations, particularly in regions reliant on wood heating. Wang et al., 2023 investigated from 2018 to 2020, BC sources in Shijiazhuang, Northern China, shifted from biomass burning in 2018 to predominantly fossil fuel combustion by 2019. BC concentrations decreased over these winters, with transport from industrial regions contributing significantly. The findings highlight the need for integrated air quality and climate measures, noting potential conflicts between BC reduction and CO_2 mitigation strategies. The US Environmental Protection Agency is preparing a comprehensive report on black carbon (BC), focusing on emission sources and mitigation strategies, both domestically and globally. In the US, diesel vehicles and engines are the main BC sources (Rao & Somers, 2010). In China, Zhang et al. (2015) used the Aethalometer ratio method in Beijing and identified a seasonal variation in BC sources, where fossil fuel combustion dominated during the summer months, while biomass burning was more significant in the winter, coinciding with residential heating activities. A similar approach was applied by Petit et al. (2015) in France, where the Abs (370nm) / Abs (880nm) ratio helped quantify the significant contributions of wood burning during the winter season, while traffic emissions were found to be the dominant source during warmer months. Further applications of the method have been found in Arctic research, where Sharma et al. (2013) used Aethalometer-derived absorption ratios to assess BC transported to the Arctic. Their results indicated that the majority of BC in the Arctic originated from fossil fuel combustion in northern Eurasia, with a minor contribution from biomass burning, a critical finding in understanding the role of BC in polar climate forcing. The Positive Matrix Factorization (PMF) method has been widely used in international studies to apportion BC sources from ambient air. Reff et al. (2007) applied PMF across several urban locations in the United States and successfully resolved BC contributions from traffic, biomass

burning, and industrial activities. They found that traffic emissions were the dominant source in urban centers, while biomass burning was more significant in rural and suburban areas. Similarly, Liu et al. (2014) used PMF in Guangzhou, China, and reported that traffic-related BC contributed over 60% to the total BC concentration, with seasonal variations showing enhanced biomass burning during the winter. In Europe, Amato et al. (2009) applied PMF in Barcelona and found that industrial sources contributed significantly to BC concentrations, particularly in the winter. The study revealed that industrial combustion sources contributed about 30% of the BC in this industrialized region. A similar study by Pekney et al. (2014) in Pittsburgh, USA, used PMF and identified significant contributions from residential wood burning, particularly during the winter months. The WRF-Chem model has also been applied extensively in source apportionment studies. Zhang et al. (2015) used WRF-Chem to simulate BC transport in the Tibetan Plateau and concluded that over 40% of the BC in this region originated from South Asian emissions, particularly from fossil fuel combustion in northern India. Similarly, Mues et al. (2017) used WRF-Chem in Europe and found that regional transport from Eastern Europe significantly contributed to BC concentrations in the western part of the continent. Radiocarbon analysis (14C) is also employed to quantify the relative contributions of biomass versus fossil fuel combustion to BC emissions (Szidat et al., 2013; Heal et al., 2011). Radiocarbon (14C) analysis is a powerful tool for distinguishing between contemporary (biomass burning) and fossil fuel sources of BC. In Europe, Szidat et al. (2013) used 14C analysis in Zurich and found that biomass burning accounted for nearly 70% of the total BC during the winter months, mainly from wood heating. Rauber et al. (2023) developed a method to separate elemental carbon (EC) from organic carbon (OC) in aerosols, effectively minimizing the charring artifact and achieving accurate 14C measurements. Zenker et al. (2017) found significant variability (28-79%) in 14C measurements of EC across nine laboratories, emphasizing the need for standardized EC isolation methods. This method provided definitive evidence of the high contribution of residential biomass burning in Switzerland. Xu et al. (2021) developed a method to analyze radiocarbon (14C) in individual dicarboxylic acids in aerosols, improving the differentiation of biomass and fossil sources and understanding of secondary organic aerosol origins. Dasari & Widory (2022) reviewed techniques for isolating black carbon (BC) from filters for 14C analysis, suggesting improvements for future methods. Similarly, Heal et al.

(2011) applied radiocarbon analysis in Glasgow, UK, and found that approximately 60% of BC was derived from biomass burning, with fossil fuel combustion being more prominent during the summer months. Mouteva et al. (2017) found that fossil fuels were the main source of black carbon (88%) and organic carbon (58%) in Salt Lake City during winter, with higher biomass contributions in summer, highlighting the need for stricter policies on mobile fossil fuels. Angyal et al. (2024) identified biomass burning as a major PM source in winter and fossil fuels in spring in Debrecen, Hungary, emphasizing the need for detailed PM source analysis. Talsma et al. (2023) created machine learning models to predict frost events with RMSE values of 1.53 to 1.72°C, using soil temperature as a key parameter, demonstrating superior performance over traditional forecasting systems. Year-long observations near Yala Glacier, Nepal, revealed that black carbon (BC) from biomass burning (44%) and fossil fuels significantly contributed to glacier mass loss (39%) by reducing surface albedo (0.8–3.8%) in the pre-monsoon season. Nepal and India were the major regional BC contributors (Gul et al., 2021).

Black carbon (BC) is a potent contributor to atmospheric radiative forcing (RF) due to its ability to absorb solar radiation. Bond et al. (2013) estimated the global direct radiative forcing of BC to be +0.88 W m^{-2} with the highest contributions from fossil fuel and biomass burning emissions. This study emphasized that the regional variations in BC RF are driven by differences in emission sources and atmospheric conditions. For instance, areas with higher emissions from fossil fuels, like China and parts of Southeast Asia, showed significantly higher RF values. The high RF in China, according to Zhang et al. (2015), was attributed to heavy industrialization and the significant contribution of coal combustion, which leads to greater BC emissions and atmospheric loading. Sharma et al. (2013) found that in the Arctic, BC transported from Eurasian regions contributes to a regional radiative forcing (+1.25 W m^{-2}). This is primarily due to its deposition on ice and snow, where BC accelerates ice melt by reducing surface albedo. Similarly, Quinn et al. (2011) highlighted the enhanced radiative forcing of BC in the Arctic, demonstrating that the combination of long-range transport and local deposition leads to warming that significantly impacts ice cover and regional climate. In Europe, Stohl et al. (2013) estimated BC RF across the continent and noted that the RF over northern Europe was lower (+0.45 W m^{-2}) than over southern Europe due to differences in emissions from fossil fuel combustion.

In southern Europe, the higher RF (radiative forcing) was associated with traffic and industrial sources, leading to significant regional warming. Research on black carbon (BC) reveals its profound impact on climate and atmospheric conditions. Chung et al., (2012) noted that BC coating increases absorption by up to 1.9 times, amplifying global forcing by 1.4 times, though effects vary with conditions. Wu et al., (2016) found that BC aging increases radiative forcing at the bottom of the atmosphere (BOA) by up to 35% while reducing it at the top of the atmosphere (TOA) by up to 100%, with effects varying by surface albedo and solar angles. Peng et al. (2016) noted faster BC aging in polluted cities like Beijing (2-4 hours) compared to cleaner cities like Houston (9-18 hours), enhancing its climate impact. Matsui et al. (2018) highlighted that uncertainties in BC emission size distributions amplify its radiative effect by 5-7 times, stressing the need for improved accuracy. Kang et al. (2020) reported accelerated cryospheric melting due to BC darkening snow and ice, particularly in the Himalayas, with increasing concentrations since the 1850s. Dou & Xiao et al. (2016) found the highest BC concentrations and radiative forcing in the Russian Arctic, with wet deposition removing over 90% of BC. Räisänen et al. (2022) showed significant BC forcing in tropical and high-latitude regions. Liu et al. (2022) observed a decline in BC absorption in eastern China, correlating with reduced emissions and an effective radiative forcing of 2.4-3.0 W m^{-2}. Kelesidis et al. (2022) found BC's light absorption enhanced by 20% from multiple scattering, leading to higher regional warming. Shi et al. (2022) showed that BC's radiative effect, particularly in the Tibetan Plateau, significantly influences snowmelt and glacier mass balance. Li et al. (2023) highlighted Brown carbon (BrC) as a significant climate factor, with a global radiative forcing of 0.03-0.57 W m^{-2}, especially in Southeast Asia and North America. Samset et al. (2014) found that a BC lifetime of less than five days is needed to match remote ocean observations, reducing estimated BC radiative forcing by 25% over the industrial era, underscoring the need for precise modelling. Atmospheric black carbon (BC) is transferred from the atmosphere to the Earth's surface through both wet and dry deposition. While wet deposition is the most effective mechanism for removing pollutants from the atmosphere, dry deposition becomes more critical in a country like India, where dry conditions prevail for most of the year (Kumar et al., 2003). Yasunari et al. (2013) reported a wide range of BC dry deposition over the southern Himalayas, from 270 to 4700 μg m^{-2}, and suggested improvements in physical modelling to reduce uncertainty to 900-

1300 μg m^{-2}. Emerson et al. (2018) measured an average dry deposition rate of refractory black carbon (rBC) at 0.3 ± 0.2 mm s^{-1} in Oklahoma, indicating a BC atmospheric lifetime of 7-11 days. Gul et al. (2024) found that 50% of dry BC deposition on the Yala glacier, Nepal, occurred during the pre-monsoon, with biomass burning and fossil fuels contributing 28% and 72%, respectively. Xu and Liu (2024) developed a method using dual-wavelength UV-visible spectroscopy to measure submicron BC deposition on plant leaves, finding concentrations of 0.01 to 1.6 mg m^{-2} in urban Nanjing, with variations among tree types. They also assessed the oxidative potential of BC on leaves, demonstrating the method's utility for air pollution monitoring. Smith et al. (2020) estimated that reducing methane and black carbon emissions could lower global temperatures by 0.18-0.26°C by 2040, with methane reductions contributing 60% of this decrease. They noted potential temperature reductions of 0.3-0.7°C and minimal additional benefits from further reductions in short-lived climate forcers. Wu et al. (2018) improved BC simulations in CAM5, leading to lower dry deposition velocities and higher BC column burdens, aligning better with observed Arctic BC concentrations and slightly increasing BC's radiative effects. Ruppel et al. (2021) found increasing BC fluxes in western Arctic Russia from 1800 to 2014, with biomass sources contributing 70% of BC and fossil fuels peaking between 1960 and 1990, highlighting the need for updated emission inventories. Ma et al. (2021) reported BC concentrations in Wuhan, China (ranging from 2.19 to 5.33 μg m^{-3}) with significant radiative forcing observed in summer. Zhang et al. (2023) analyzed 40 years of MERRA-2 data, finding an average dry deposition flux of 0.00059 ± 0.00014 μg m^2 s^{-1} and a velocity of 0.00051 ± 0.00004 m s^{-1}, with significant regional and seasonal variations. Higher fluxes were noted in the northern China Plain and Sichuan Basin, and larger velocities in the Tibet Plateau. Lapere et al. (2023) observed that BC deposition on central Chilean Andes glaciers was four times higher in winter, affecting low-elevation glaciers,and stressed the need to control summertime emissions from Santiago.

Predicting black carbon (BC) concentrations and their spatiotemporal variability is essential for understanding their environmental and climatic impacts. Various models have been developed to predict BC levels, each employing different methodologies and incorporating diverse datasets. Ganguly and Bras (2003) integrated radar and numerical weather prediction for improved short-term precipitation forecasting, paving the way for more accurate climate modeling. Building on this, Khan

et al. (2005) explored chaos detection in hydrological time series, emphasizing the complexity of identifying chaotic components amidst noise and seasonality. Steinhaeuser et al. (2009) introduced complex networks for climate data analysis, enhancing interpretability compared to traditional clustering methods. Later, Mishra et al. (2014) assessed the reliability of global climate models (GCMs) and regional climate models (RCMs) in simulating precipitation extremes over India, highlighting ongoing challenges in accurate projections. Expanding on predictive modeling, Vandal et al. (2019) & Kodra et al. (2020) compared traditional statistical downscaling with advanced machine learning techniques, revealing inconsistent performance in capturing climate extremes. Collectively, these studies demonstrate the evolving role of data science and machine learning in enhancing climate predictive models. Time series models, such as ARIMA (Auto Regressive Integrated Moving Average), have been utilized for BC prediction due to their effectiveness in capturing temporal patterns. Li et al. (2018) applied ARIMA models to forecast daily BC concentrations in urban areas of China, achieving satisfactory accuracy by incorporating historical BC data and meteorological variables. Similarly, Gao et al. (2017) used ARIMA to predict BC levels in Northern Europe, demonstrating the model's ability to account for seasonal variations. Random Forest (RF) and eXtreme Gradient Boosting (XGBoost) are advanced machine learning techniques that have been increasingly employed for BC prediction due to their robustness and accuracy. Zhang et al. (2019) employed RF models to predict BC concentrations in Beijing, achieving high predictive performance by incorporating multiple features such as meteorological data and emission sources. Liu et al. (2020) utilized XGBoost to model BC levels in India, finding that the model provided superior accuracy compared to traditional regression methods by effectively handling nonlinear relationships and interactions among predictors. Support Vector Regression (SVR) and artificial neural networks (ANNs) are also prominent in BC prediction. Cheng et al. (2019) used SVR to predict BC concentrations in Eastern Asia, demonstrating the model's capability to capture complex patterns and improve prediction accuracy. Lee et al. (2021) applied a Multilayer Perceptron (MLP) neural network to forecast BC levels in South Korea, noting that ANNs could model the nonlinear dependencies between BC and meteorological variables effectively. The Weather Research and Forecasting model coupled with Chemistry (WRF-Chem) is widely used for BC prediction on regional scales. Grell et al.

(2005) introduced WRF-Chem as a tool for simulating the interactions between atmospheric chemistry and meteorology. Wang et al. (2016) utilized WRF-Chem to assess BC distribution and transport in East Asia, incorporating emission inventories and meteorological data to improve prediction accuracy. The model's ability to simulate atmospheric processes and interactions makes it a valuable tool for understanding BC dynamics. The Community Multiscale Air Quality (CMAQ) model has been applied to BC prediction in various regions. Byun & Schere (2006) described the CMAQ model's framework for simulating air quality and BC levels. Huo et al. (2019) used CMAQ to analyze BC concentrations over the United States, emphasizing the model's capability to integrate emission sources, meteorological conditions, and chemical reactions to predict BC levels accurately. Hybrid models that combine statistical and chemical transport approaches offer enhanced predictive capabilities. Zhu et al. (2020) integrated machine learning techniques with chemical transport models to improve BC prediction in urban areas of China. The study highlighted that combining different methodologies could provide the strengths of both approaches, leading to more accurate and reliable predictions. Mahmud et al. (2022) showed that machine learning models, particularly random forest, effectively predict $PM_{2.5}$ concentrations with 92% accuracy, identifying risky areas. May and Li, (2022) found that support vector machines (SVM) were least sensitive to input variable variations but less accurate when Ångström exponents were below one. This research highlights the evolution of carbonaceous aerosol analysis by AMS. Yadav et al. 2024 developed a globally scalable approach to estimate air quality (AQ) in data-poor regions using satellite imagery (SI) and machine learning (ML). By adapting ML-AQ models from data-rich to data-poor regions, the method enables accurate AQ estimation without extensive ground infrastructure. A case study in Accra, Ghana, demonstrated that the trained model can explain up to 54% of the variation in AQ distribution without target labels. Zhnag et al., 2019 reported that Local weather conditions were more influential than emission changes, with non-local trucks raising BC emissions by 60% and concentrations by ~2 μg m^{-3}. The study suggests stricter controls for these trucks and considers midday access based on weather forecasts. Bond et al. (2013) found that implementing black carbon mitigation measures can significantly reduce Arctic warming. Similarly, Kopp and Mauzerall (2010) analyzed the benefits of mitigating black carbon emissions from contained combustion sources and found that failing to reduce

carbonaceous aerosol emissions from these sources would require CO_2 emission cuts about 8 years (range of 1to 15 years) earlier than would be necessary with full mitigation of these emissions in order to achieve the 500 ppmv CO_2 equivalent. Anenberg et al. (2012) found that black carbon mitigation can reduce Arctic warming by up to 0.27°C by 2050 and reduce premature deaths from air pollution by up to 150,000 annually. Machine learning offers a powerful approach for monitoring, assessing, and managing metal pollution across environmental matrices (Nkinahamira et al., 2024). A study by Li et al. (2024) proposed an emission- based machine learning approach for large-scale estimates of black carbon concentrations over China, and found that the Random Forest algorithm showed the best performance. Wang et al. (2021) used an explicit emission tagging method in global modelling of source-receptor relationships for black carbon in the Arctic, and found that the model accurately estimated the seasonal-averaged black carbon concentrations.

National Status

Several studies have documented the variability in concentration, sources and impacts of black carbon (BC) across different regions of India. India is the second-largest BC emitter in the world (Bond et al., 2013) with emission estimates ranging from 400 Gg y^{-1} in 1997 (Reddy and Venkataraman, 2002) to 901 Gg y^{-1} in 2011 (Paliwal et al., 2017). There exist, however, large variations in BC emission estimates from India; for example: Sahu et al. (2023) estimated an emission of 1300 Gg y^{-1} in 2001, while the Greenhouse Gas – Air Pollution Interactions and Synergies (GAINS) and the Speciated Pollutant Emissions Wizard (SPEW) estimates for 2000 were 500-580 Gg y^{-1}.

Black carbon (BC) measurement is a crucial aspect of understanding its impact on climate and air quality in India. Several studies have employed various techniques to measure BC concentrations in different regions of India. Atmospheric dust in India influences air quality, climate, and biogeochemical cycles, with both positive and negative environmental impacts (Kumar et al., 2004; Kulshrestha & Jnu-Eiacp, 2021). High black carbon (BC) exposure in the Indo-Gangetic Plain (IGP) significantly impacts public health, contributing to 62% of cardiovascular mortality in megacities and 49% in semiurban areas. Targeted emission reductions from biofuel, diesel, and coal combustion could potentially save over 400,000 lives annually (Verma et al., 2022). Shipborne measurements over the northern Indian Ocean (NIO) during winter 2018 revealed that South Asian outflow was dominated by

biomass-burning and combustion-related aerosols. Fine-mode aerosols contained high levels of elemental carbon, sulfates, and potassium, while organic aerosols were rich in sugars and plastic combustion products. Brown carbon absorption was twice as high in the South Asian outflow, mainly from biomass-burning emissions (Boreddy et al., 2021). A study by Malik et al. (2022) used a thermal-optical analyzer to measure BC concentrations in Delhi and found that regional transport, meteorology, and local sources contributed to pollution episodes. Additionally, a study by Cheng et al., (2011) compared two thermal-optical methods for the determination of organic carbon and elemental carbon in aerosols collected from the southeastern United States and India. These studies have contributed significantly to our understanding of BC measurement techniques in India and have paved the way for further research in this area. The aethalometer is a widely used instrument for measuring black carbon (BC) concentrations in India. Several studies have employed this instrument to measure BC concentrations in different regions of India. Sahu et al. (2013) used an Aethalometer to measure BC concentrations in Bhubaneswar, Odisha, and found that the city's BC concentrations were influenced by local sources, such as vehicular emissions and biomass burning. Additionally, a study by Beegum et al. (2012) used an Aethalometer to measure BC concentrations in Hyderabad, Telangana, and found that the city's BC concentrations were influenced by regional transport and local sources. The results indicated that BC concentrations were significantly higher in Delhi than in Mumbai, highlighting the need for targeted emission control strategies. Kiran et al., 2019 developed an empirical method using Aethalometer data to quantify black carbon (BC) sources across five locations in India. The method, named the "Two Alpha Method," identifies fossil fuel as the dominant BC source (~70%) regardless of location. This approach offers a reliable way to assess spatiotemporal variability in BC sources and can be applied widely to inform mitigation strategies. In India, black carbon (BC) concentrations vary significantly across urban, suburban, and rural areas. Urban centers show extreme levels: Allahabad reports 15-50 µg m^{-3} (Badarinathet al., 2007), New Delhi ranges from 2.4 to 15.9 µg m^{-3} (Surendran et. al., 2013; Saraswat et al., 2013), and Kanpur reaches up to 12 µg m^{-3} (Nair et al., 2007), reflecting severe pollution. In contrast, Goa has lower levels at 0.3 µg m^{-3} (Menon et al., 2010). Suburban areas have intermediate BC concentrations, with Agra at 10.4 µg m^{-3} (Safai et al., 2007), Chennai ranging from 3.8 to 11.2 µg m^{-3} (Aruna et al., 2013), and Patiala between 5.0 and

25.0 μg m^{-3} (Sharma et al., 2012; Kharol et al., 2012). Rural areas generally have lower levels, such as Tirupati (0.5-1.0μg m^{-3}) and Sinhagad (0.8-2.2 μg m^{-3}) (Hussain et al., 2017). However, Varanasi shows elevated levels of 10.6 μg m^{-3} (Sateesh et al., 2011), and Agartala shows 9.35 μg m^{-3} (Guha et al., 2015), often due to local biomass burning and agricultural activities. Black carbon (BC) concentrations across India have been extensively studied due to their severe impacts on air quality, public health, and climate. These studies often focus on the diurnal, seasonal, and annual patterns, highlighting the factors influencing BC levels, including meteorology, emissions, and human activities. The findings from various papers emphasize the variation in BC concentrations across different regions and timeframes. Several studies have shown that BC concentrations in Indian cities exhibit distinct diurnal patterns, often peaking during morning and evening hours. Babu et al. (2013) studied BC concentrations in Trivandrum, observing that levels were highest during the early morning due to temperature inversions and increased vehicular emissions. Beegum et al. (2008) reported similar trends in Pune, where morning and evening peaks coincided with rush hours, followed by lower concentrations during midday when atmospheric mixing improved. These findings have been consistent across several Indian cities, with BC levels influenced by traffic, biomass burning, and meteorological conditions during different times of the day. Seasonal variability of BC concentrations is significant, with higher levels generally recorded in winter months. Latha and Badrinath (2005) investigated BC levels in Hyderabad and found that concentrations were highest during the winter due to lower boundary layer height, stagnant conditions, and increased biomass burning. In contrast, monsoon months see the lowest concentrations due to rainfall scavenging and wet deposition, as shown by Gadhavi and Jayaraman (2010) in their study of Ahmedabad. Nair et al. (2007) further documented how winter conditions enhance the accumulation of pollutants, leading to elevated BC levels across northern India, particularly in cities like Delhi and Kanpur. The annual trends of BC concentration vary depending on urbanization, industrialization, and pollution control measures. Tiwari et al. (2013) analyzed the long-term BC trends in Delhi and found a significant increase in concentrations from 2000 to 2010, primarily due to rapid industrial growth and vehicular emissions. Sahu et al. (2015) noted similar trends in Mumbai, with a gradual rise in BC levels over time, although recent efforts in pollution control have led to stabilization in certain areas. Dumka et al. (2010) found

that in the foothills of the Himalayas (Nainital), BC levels were lower compared to urban centres but showed an upward trend due to regional pollution transported from the Indo-Gangetic Plain. The primary drivers of elevated BC concentrations in India are vehicular emissions, industrial activities, and biomass burning. During winter, meteorological conditions such as lower temperatures, lower boundary layer height, and weak winds trap pollutants near the surface, resulting in higher BC levels, as reported by Safai et al. (2013)**.** Biomass burning, particularly during the post-monsoon and winter seasons, further contributes to elevated BC levels, especially in northern India, as seen in studies by Srivastava et al. (2012) and Sharma et al. (2017)**.** BC concentrations vary significantly across regions. Ramachandran and Kedia (2010) documented how the Indo-Gangetic Plain (IGP) consistently experiences the highest BC levels due to dense population, industrial activities, and agricultural residue burning. Cities like Delhi, Kanpur, and Lucknow see consistently high levels of BC throughout the year, with peaks in winter. Winter black carbon (BC) in northeast India, dominated by fossil fuel (70%) and biomass burning (30%) significantly impacts air quality and health, with exposure equivalent to 25 passive cigarettes per day. Brown carbon (BrC) from open biomass burning contributes notably to aerosol light absorption, peaking during winter nights (Singh & Gokhale, 2021). In contrast, southern cities like Bengaluru and Chennai exhibit lower BC levels, as observed by Reddy et al. (2012), due to less industrialization and better dispersion of pollutants. Mishra & Kulshrestha (2021) demonstrate that the char-EC/soot-EC ratio is a more effective tracer for distinguishing biomass burning and fossil-fuel combustion impacts on carbonaceous aerosols in the Central Indo-Gangetic Plain. Ambade et al. (2022) presents the first inventory of $PM_{2.5}$-bound chemical concentrations and black carbon profiles in middle-east India, highlighting their sources and health implications. It reveals significant contributions from fossil fuel combustion and wood burning, emphasizing the need for further research. Gupta et al. (2017) examined BC in Agra, India, noting a mean concentration of 9.5 μg m^{-3} with significant seasonal and diurnal variations. This work was expanded by Gupta et al. (2023), who compared BC levels during the COVID-19 lockdown with those from the previous year, finding a significant reduction in BC concentrations due to decreased emissions from transportation and industry. Mehrotra et al. (2023) conducted a 13-year study in Varanasi, revealing a mean daily BC concentration of 9.18±6.53 μg m^{-3} with a decreasing trend of -

0.47 μg m^{-3} yr^{-1}, particularly during the post-monsoon season. They have also reported significant radiative forcing effects, with a decreasing trend at the top of the atmosphere but an increasing trend at the surface. In Pune, Safai et al. (2007) and later Safai et al. (2013) conducted long- term studies, reporting an annual average BC concentration of 4.1 μg m^{-3}, with highest levels during winter and lowest during the monsoon season. Their work highlighted the influence of meteorological parameters and the correlation of BC with fine particulate matter ($PM_{1.0}$) and other anthropogenic aerosol components. Tripathi et al. (2005) focused on Kanpur, where high BC concentrations (6-20 μg m^{-3}) during December 2004 led to strong surface cooling (-62 W m^{-2}) and atmospheric heating (+71 W m^{-2}), comparable to levels in other Indian mega cities but higher than in Europe, the USA, and other parts of Asia.

Indoor black carbon (BC) measurements in rural Eastern India showed the highest concentrations in closed kitchens (477.25 μg m^{-3}) and the lowest in open kitchens (260.14 μg m^{-3}), with biomass burning as the dominant source (Hussain et al., 2023).

In India, several studies have documented significant BC radiative forcing, particularly in regions like the Indo-Gangetic Basin (IGB). This may be largely due to the combination of biomass burning and fossil fuel emissions from transportation. The IGB, as a densely populated and industrially active region, experiences high BC concentrations, which contribute to elevated RF values. Anthropogenic biomass burning in India, including crop residue burning, waste burning, and forest fires, significantly impacts air quality, visibility, and health. Its spatio-temporal variations necessitate region-specific, airshed-based management strategies for effective mitigation (Tripathi et al., 2024). According to Ramanathan and Carmichael (2008), BC emissions in India from residential biomass burning and vehicular traffic play a crucial role in the high radiative forcing observed, particularly during the winter when atmospheric stability allows for the accumulation of aerosols. In southern India, Satheesh et al. (2011, 2016) reported lower BC RF (+1.5 W m^{-2}) in comparison to northern India due to differences in emission sources. Southern India experiences relatively lower biomass burning and industrial emissions, which accounts for the reduced RF. However, during the monsoon season, the region's RF decreases further due to aerosol washout by rain, as observed by Nair et al. (2014). The Himalayan region also exhibits unique BC RF characteristics. Pant et al., (2016) measured BC

radiative forcing in the central Himalayas and found values of +3.0 W m^{-2}, with BC deposition on snow and glaciers contributing significantly to the melting of the ice surfaces. The study emphasized that long-range transport from northern Indian plains contributes to the high BC levels and subsequentRF in the region. Tripathi et al., 2005 recorded high black carbon levels (6–20 μg m^{-3}) with significant atmospheric absorption (+71 W m^{-2}) and a heating rate of ~1.8°K day^{-1} in Kanpur, suggesting potential regional climate impacts due to pronounced surface cooling and atmospheric heating. Babu et al. (2002) conducted a field campaign in Bangalore, revealing that BC accounted for 11% of total aerosol mass and 23% of sub-micron mass, resulting in significant radiative effects, including a surface forcing of -23 W m^{-2} and an atmospheric heating of 0.8-1.5 K day^{-1}. Ramachandran and Rajesh (2007) observed diurnal and seasonal variations in BC concentrations in Ahmedabad. The higher levels were found during winter (5 μg m^{-3}) and lower during summer (0.8 μg m^{-3}) due to changes in boundary layer height and convective activity. Rehman et al. (2011) studied rural India, where indoor BC concentrations during cooking hours using traditional stoves peaked at 1000 μg m^{-3}, far exceeding outdoor levels and highlighting the underestimation of BC loading by satellite studies. Mahapatra et al. (2014) investigated Bhubaneswar and found a winter maximum in BC concentrations (5.6 μg m^{-3}) influenced by stable atmospheric conditions and long-range transport, with fossil fuel combustion identified as the dominant BC source. Rana et al. (2019) reviewed BC measurements in India from 2002 to 2018.

In India, several studies have employed the two-wavelength aethalometer technique to investigate BC sources. Srivastava et al. (2012) applied the method in Delhi and found that traffic emissions were the dominant source of BC, especially during the winter season, with the Abs (370nm) / Abs (880nm) ratio indicating significant biomass burning during the post-monsoon and winter seasons due to agricultural residue burning. The WRF-Chem model has also been used in India to simulate BC sources and transport. BC in the Indo-Gangetic Basin and found that emissions from biomass burning contributed significantly during the post-monsoon and winter seasons, while fossil fuel sources dominated during the summer (Gogoi et al., 2021). The study underscored the importance of regional emissions and long-range transport in shaping BCconcentrations in this densely populated region.

Retrieval of black carbon (BC) from satellite remote sensing has been an active area of research in

recent years. Several studies have demonstrated the potential of satellite-based approaches for estimating BC concentrations. For instance, a study by Dehkhoda et al. (2020) utilized AERONET-retrieved depolarization ratio, single scattering albedo, and Ångström Exponent to estimate the contribution of BC to the absorbing fractions of aerosol optical depth (AOD) over East Asia (Dehkhoda et al., 2020). Another study by Bao et al. (2019) developed a method to retrieve BC surface concentrations using satellite remote sensing observations, achieving a high correlation coefficient of 0.85 with ground-based measurements (Bao et al., 2019). Furthermore, a study by Liu et al. (2017) used MODIS products to estimate BC concentrations over Beijing, China, and found a good agreement with in situ measurements. Additionally, MERRA-2 reanalysis data has been used to retrieve BC concentrations, providing a high-resolution dataset for air quality monitoring and climate modelling (Gelaro et al., 2017). These studies demonstrate the potential of satellite remote sensing for retrieving BC concentrations and emissions, which can be useful for air quality monitoring and climate modelling. Dey et al., 2006 retrieved black carbon (BC) concentrations over Kanpur (2001–2003) using AERONET data, revealing seasonal variations with higher BC in post-monsoon and winter. The method, incorporating the effects of organic carbon (OC) and dust, aligned well with in situ measurements, offering a viable approach for global BC and OC absorption estimation. Smaran & Vinoj, 2024 quantifies background black carbon (BC) levels over India, finding that background BC consistently exceeds 75% annually, peaking in winter (86%, 2.32 μg m^{-3}) and dipping during the monsoon (79%, 0.60 μg m^{-3}). The method, validated with ground-based and reanalysis data, reveals spatial patterns similar to BC emission inventories, underscoring the significant role of background BC pollution and aiding policymakers in addressing air quality issues.

A small-scale investigation of dry deposition has been done in India. According to Suman (1989), dry deposition monitoring was conducted throughout central Panama to gather particles created during the period of agricultural burning. Kumar, 2002; measured the dry deposition flux of major ions over the natural surfaces like leaves, marble, etc. The determination of the black carbon aerosol scavenging coefficient was reported by Latha & Badrinath (2005) using ground-based data over an urban area of Hyderabad from January to December 2004. The parameterization process of dry deposition of S compounds on a natural surface (marble) and a direct measurement of dry deposition on vegetation

was also carried out in Agra (Kumar et al., 2002 & 2003). According to research done in 2013 by Nair et al., 2014 absorbing aerosols like dust or black carbon (BC) over high-altitude Himalayan regions (Hanle and Nepal Climate Observatory-Pyramid) may have an impact on the hydrological cycle and regional climate over South Asia. For a broad range of dry deposition velocities (0.01-0.054 cm s^{-1}) of BC, snow depths (2-10 cm), and snow densities (195-512 kg m^{-3}), the estimated amount of BC in the snowvaried from 117 to 1.7 µg kg^{-1}. Gupta (2021) developed a model to estimate the dry deposition velocity and flux of black carbon. The dry deposition flux of black carbon inferred using the theoretical method was comparable to the value obtained by the direct measurement method.

In India, predicting black carbon (BC) concentrations is crucial due to the high levels ofpollution and its significant impact on air quality and climate. Very few have applied various prediction models to assess BC levels, utilizing statistical, machine learning, and chemical transport approaches. Time series models like ARIMA have been employed to forecast BC concentrations in Indian cities. Satpathy et al. (2024) explored machine learning (ML) methods for predicting BC concentrations, identifying XGBoost as the most effective model, with temperature and wind speed as key influencing factors. Research has consistently shown that machine learning and artificial intelligence models can be effective in predicting black carbon concentration in India. Rovira et al., 2022 developed non-linear models for black carbon exposure modelling using air pollution datasets in India and found that the models can accurately predict black carbon concentrations. Furthermore, a study by Batterman et al., 2020 used Bayesian data fusion and dispersion modelling to enhance models and measurements of traffic-related air pollutants, including black carbon, in India.

A significant knowledge gap remains in India regarding black carbon dynamics and its regional impacts. Unlike abroad, where studies have employed advanced techniques such as radiocarbon analysis for precise source interpretation, such research is lacking in India. Furthermore, most Indian studies on BC have been limited to major urban cities due to the highcost of measurement equipment. Notably, India still lacks standardized protocols for BC measurement, despite its significance as a climate pollutant. This underscores the urgent need for comprehensive research on BC in India, particularly in the context of climate change mitigation and adaptation.

OBJECTIVE

Black carbon (BC), recognized as the second most significant contributor to global warming, poses serious challenges to both climate and public health. India, one of the major global emitters, has regions like the Indo-Gangetic Basin (IGB) that rank among the top seven BC emission hotspots worldwide. Despite this, research efforts have predominantly concentrated on urban areas, leaving a critical knowledge gap in suburban/rural regions, whereair pollution and BC levels are also on the rise. The complexity and high cost of BC measurement instruments often led to limited data collection in selected areas. It has posed challenges to assess long-term trends, understand BC's role in radiative forcing, develop effective mitigation strategies, and accurately predict future concentrations.

Agra, a city known for its severe air pollution, exemplifies such a challenge. Positioned within the IGB and surrounded by significant industrial sources, Agra faces escalating BC emissions that threaten both the environment and public health. The city's proximity to major industrial activities, such as the Mathura refinery and the Firozabad glass industry, further exacerbates the situation. Additionally, the presence of the Taj Mahal, a UNESCO World Heritage Monument, amplifies the urgency of addressing BC pollution to protect this cultural landmark from further degradation. Hence, there is an immediate need for a comprehensive study on BC in Agra. This research must include precise source attribution, extensive long-term data collection, and an in-depth analysis of BC deposition flux. Such efforts are essential for developing effective emission reduction strategies and safeguarding both public health and the environment. By focusing on under-researched regions and scaling up monitoring efforts, this study aims to fill critical gaps in BC knowledge, ultimately contributing to more informed climate policies and protective measures. With these considerations in mind, the objectives of the present investigation are:

- to measure black carbon concentration, $PM_{2.5}$ concentration and meteorological parameters to analyze annual, seasonal and temporal patterns at a sub-urban site in Agra region over Indo-Gangetic Basin,
- to identify the sources of black carbon,
- to estimate dry deposition flux of black carbon,
- to develop the prediction model of black carbon utilizing the long-term datasets and
- to set paradigms for mitigation of black carbon through a survey-based approach.

3. METHODOLOGY

The present study will be carried out in Agra over Indo-Gnagetic Basin.

3.1 Site Description: Agra (27.17° N, 78° E) lies majestically in the heart of northern India, situated inside the vast Indo-Gangetic Basin. The Indo-Gangetic basin, spanning one-fifthof India's landmass, is characterized by high population density and heightened human activities driven by growth in the economy and population (Nair et al., 2007). Agra is also historically significant. It is known for being the city of the Taj Mahal, one of the Seven Wonders of the World. Agra has a population of 1,775,130 according to the 2011 census. It has a continental subtropical climate with summer temperatures ranging from 21.9ºC to 40ºC and winter temperatures from 4.2ºC to 31.7ºC.

Agra, located around 200 kilometers south of New Delhi and 363 kilometers west of Lucknow, is an environmentally significant city because of its unique geographical location. It is located at the intersection of three separate geophysical regions: the plains of Uttar Pradesh, the plateaus of Madhya Pradesh, and the Thar Desert of Rajasthan, which covers two-thirds of its perimeter. This location makes Agra not just a cultural crossroads, located in the heart of Braj, Bundelkhand, Rajputana, and western Uttar Pradesh, but also an essential destination for environmental research.

In Agra, major sources of air pollution include automotive emissions, diesel generators, road dust, residential cooking, and industrial activities, notably from textiles, chemicals, leather, and foundries. The city also faces pollution from the local production of 'Petha' sweets, which relies heavily on coal. Nearby Firozabad's glass industry and the Mathura Refinery, 50 kmaway, further contribute to the pollution. Additionally, National Highway 19 (NH-19) adds to vehicular emissions. These combined sources make Agra a key area for studying the impacts of air pollution, especially black carbon, over the Indo-Gangetic Basin.

In Agra, the sampling will be performed at Dayalbagh, a suburban site that is 10 km away from the industrial sector of the city. The sampling process will be performed on the roof of a double-story building (8 m above the ground) in the campus of Dayalbagh Educational Institute (Deemed to be University), Dayalbagh, Agra. The sampling site is located at a distance of 2 km from the national highway NH-19, which has dense vehicular traffic.

3.2 Black Carbon Measurement: A seven-channel Aethalometer (Model AE33; Magee Scientific

USA) will be used to assess the concentration of Black Carbon (BC). This device, renowned for its accuracy, measures the concentration of BC once every minute using the optical attenuation method. The Aethalometer drew in ambient air through its input tube at a consistent flow rate of 2 liters per minute (LPM). Throughout this procedure, the aerosol particles get continuously gathered on a filter tape. The Aethalometer employed the principle of transmission, which was first introduced by Hansen et al. in 1984, to measure optical absorption through continuous filtration through a quartz filter. The Aethalometer recorded data at seven wavelengths (370, 470, 520, 590, 660, 880, and 970 nm). It is generally acknowledged that the measurement of absorbance at 880 nm is a reliable predictor of the concentration of BC (Satheesh et al., 2003; Pant et al., 2006; Gupta et al., 2023). The sampling will be done for a period of two consecutive years.

3.3 Fine Particulate Matter ($PM_{2.5}$) Measurement: Fine Particulate Matter ($PM_{2.5}$) samples will be collected using Envirotech Fine Particulate samplers, APM 550. The starting weight (W_1) of the clean, dry filter will be taken by using a precision analytical balance with suitable sensitivity. The samplers will be fitted with Poly Tetra Fluoro Ethylene (PTFE) / Quartz filter sheets, and the sampling will be done for 24 hr at a flow rate of 1.1 m^3 min^{-1} to get a representative sample of aerosols. After the sampling, the filter from the sampler will be placed in a desiccator to remove any moisture before weighing. Once the filter reaches a constant weight (W_2) after the desiccator process, the concentration will be calculated.

The PM concentration will be calculated using the following formula:

$$\text{PM concentration } (\mu g\ m^{-3}) = ((W_2 - W_1) / V)$$

Where:

W_2 = Weight of the filter after sampling and desiccator process (μg)

W_1 = Initial weight of the filter before sampling and desiccator process (μg)

V = Volume of air sampled (m^3)

Fine particulate matter ($PM_{2.5}$) samples will be collected once a week.

3.4 Characterization of Aerosol Sample: A representative number of samples of $PM_{2.5}$ will be analyzed using ion chromatograph (Dionex DX 1000), field emission scanning electron microscope coupled with energy-dispersive X-ray analysis (JEOL JSM-IT800), and inductively coupled plasma-

mass spectrometry (ICP-MS) for major ions. One-fourth of each filter will be cut into small pieces and extracted in 25 ml deionized water, and the other one-fourth will be cut and extracted in 25 ml dilute nitric acid on an electrical shaker, followed by half an houron ultrasonic bath for analysis of water-soluble major inorganic ions (Na^+, K^+, Ca^{2+}, NH_4^+,Mg^{2+}, F^-, Cl^-, NO_3^-, SO_4^{2-}) and acid-soluble ions, respectively. For FESEM analysis, the filter will be cut into 1 mm × 1 mm pieces to attach to stubs with carbon tape and will be coated with a thin layer of platinum (JEOL Platinum Coater) to obtain the shape and size of particles and elemental analysis.

3.5 Measurement of Meteorological Parameters: Meteorological parameterswill be monitored using an Automatic Weather Station (AWS) 10.0 (M/s Rave Innovations, Noida), which provides real-time data through sensor-based measurements; it employs a thermistor for temperature, a capacitive sensor for relative humidity, an anemometer for wind speed, a wind vane for wind direction, and a pyranometer for solar radiation, each precisely capture its respective atmospheric parameter. AWS is a microprocessor-based wind recording system with an inbuilt clock and calendar. The data logger acquires data from the sensors for wind speed, wind direction, air temperature, and solar radiation and stores the data in its memory for later retrieval as well as displaying the data to monitor. The global radiation will be monitored by using a pyranometer (M/s Delta Ohm, Italy). These global radiations lie in the range of 300-2800 nm.

3.6 Source Identification of Black Carbon: Source identification is a vital component to curb down the black carbon (BC) emissions and mitigate their impact on the environment. By pinpointing the sources of BC, policymakers and stakeholders can develop targeted strategies to curb emissions and mitigate the environmental and health burdens associated with this potent pollutant. In this study, the source of black carbon will be identified by the Angstrom Exponent method, Positive Matrix Factorization, and Radiocarbon (14C) analysis.

3.6.1 Angstrom Exponent Method for Source Interpretation: Black carbon (BC) at 370 nm and 880 nm wavelengths can be used to determine the potential sources of BC, which can be used as an indicator of local sources such as fossil fuel and biomass burning (Kirchstetter et al., 2004; Zhang et al., 2011; Wang et al., 2014; Gupta et al., 2017).

The percentage fractionation of BC will be determined based on the Sandradewi et al. (2008)

model. According to this model, the aerosol optical absorption coefficient is a sum of biomass burning and fossil fuel combustion fraction contributions to aerosol absorption, featuring specific values of the Absorption Angstrom Exponent (AAE). The two sources (fossil fuel and biomass burning) follow λ^{-1} and λ^{-2} spectral dependencies, respectively (Kirchstetter et al., 2004; Sandradewi et al., 2008; Favez et al., 2010).

$$\frac{b_{abs}(\lambda 1)_{ff}}{b_{abs}(\lambda 2)_{ff}} = \left(\frac{\lambda 1}{\lambda 2}\right)^{-\alpha ff} \quad \text{(i)}$$

$$\frac{b_{abs}(\lambda 1)_{bb}}{b_{abs}(\lambda 2)_{bb}} = \left(\frac{\lambda 1}{\lambda 2}\right)^{-\alpha bb} \quad \text{(ii)}$$

The determination of fractionation of β_{bb} (biomass) at 880 nm and β_{ff} (fossil fuel) at 370 nm hasbeen calculated by using the following equation;

$$b_{abs}(\lambda) = b_{abs}(\lambda)_{ff} + b_{abs}(\lambda)_{bb} \quad \text{(iii)}$$

where, β_{ff} is the spectrally dependent mass absorption efficiency at 880 nm and β_{bb} is the spectrally dependent mass absorption efficiency.

$$BB(\%) = \frac{b_{abs}(\lambda 2)_{bb}}{b_{abs}\,(\lambda 2)} \quad \text{(iv)}$$

$$BC_{bb} = BB * BC \quad \text{(v)}$$

$$BC_{ff} = (1 - BB) * BC \quad \text{(vi)}$$

The concentrations of light-absorbing carbon particles at different wavelengths obtained from the aethalometer will be averaged to obtain the concentration of the light-absorbing carbon particle. The BC_{ff} close to 1 and BC_{bb} close to 2 have been observed by several researchers (Sandradewi et al., 2008; Herich et al., 2011; Zotter et al., 2017; Liakokou et al., 2019; Gupta, 2021).

3.6.2 Positive Matrix Factorization model: The Positive Matrix Factorization (PMF) model is a statistical tool used to identify sources of black carbon aerosols by analyzing the chemical composition of aerosols. It assumes that observed data can be explained as a combination of underlying factors, each representing a specific pollution source. PMF processesdata on various chemical species to reveal patterns and correlations, thereby identifying the sources of black carbon (Bibi et al., 2021).

3.6.3 Radiocarbon (14C) Analysis: Radiocarbon analysis, also known as 14C analysis, is a highly sensitive and precise technique used to determine the origin and age of organic materials, including

black carbon (BC). In the context of BC research, 14C analysis will be employed to distinguish between fossil fuel-derived and biomass-derived emissions, providing valuable insights into the sources of BC in the atmosphere (Kontul' et al., 2020).

The Accelerator Mass Spectrometry (AMS) Facility of IUAC, New Delhi, will be used to analyze the 14C content of BC samples. AMS is a highly sensitive and precise technique that uses a particle accelerator to count the individual 14C atoms in a sample. Sample preparation for Accelerator Mass Spectrometry (AMS) involves collecting and cleaning the sample, purifying it to isolate carbon, converting it to graphite, and analyzing it using AMS to measure 14C levels. The resulting data will be used to calculate the sample's age and interpret its significance.

Fraction Modern (Fm) Value

The fraction modern (Fm) value is a critical parameter in 14C analysis, representing theratio of 14C to total carbon in a sample. The Fm value can be calculated using the following equation:

$$Fm = (^{14}C/^{12}C)\ sample\ /\ (^{14}C/^{12}C)\ modern$$

Where, ^{14}C and ^{12}C are the concentrations of radiocarbon and stable carbon, respectively, in the sample and modern standards.

The Fm value ranges from 0 to 1, with values close to 1 indicating a modern, biomass-derived source, and values close to 0 indicating a fossil fuel-derived source. Fm values between 0 and 1 indicate a mixture of both sources.

3.7 Dry Deposition Flux of Black Carbon

Dry deposition flux (F_d) will be calculated by inferential method using the following formula:

$$F_d = V_d * C$$

where:

F_d = dry deposition flux ($\mu g\ m^{-2} s^{1}$)

V_d = deposition velocity ($m\ s^{-1}$)

C = BC concentration ($\mu g\ m^{-3}$)

The concentration obtained from the aethalometer will be multiplied by dry depositionvelocity of black carbon (available in the literature) (Gupta, 2021).

3.8 Modelling and Prediction of Black Carbon

The long-term data of BC will be utilized to predict and forecast the black carbon concentration using artificial intelligence / machine learning / soft computing.

3.8.1 Artificial Intelligence / Machine Learning / Soft Computing

Artificial Intelligence (AI), Machine Learning (ML), and Soft Computing will play crucial roles in predicting black carbon (BC) concentrations, offering advanced methodologies that enhance accuracy and efficiency. AI simulates human intelligence processes, enabling machines to learn from data, reason, and self-correct, which is essential for analyzing complex environmental data. ML, as a subset of AI, focuses on identifying patterns in data and making predictions or decisions without explicit programming. This capability allows models to improve over time as they will be exposed to more data, leading to increasingly accurate predictions of BC levels. Soft computing, which encompasses approaches like fuzzy logic, neural networks, and evolutionary algorithms, excels in managing uncertainty, approximation, and imprecision, common challenges in environmental modelling. These techniques will develop robust models that accurately predict BC concentrations, identify pollution sources, and support effective mitigation strategies, ultimately contributing to better air quality and climate Protection.

To predict and forecast black carbon, AI/ML tools will be employed alongside soft computing models for validation. The process involves collecting data on air pollution and meteorological parameters from existing networks, including $PM_{2.5}$, relative humidity, solar radiation, temperature, wind speed, wind direction, and black carbon mass concentrations. The data will be pre-processed, including handling missing values, outlier removal, normalization, and scaling. Feature engineering/ML algorithms will extract relevant meteorological and air pollution parameters. Initially, data of the last 10 years of black carbon, aerosol, and meteorological parameters collected at Agra will be trained, and forecasts will be made for the next two years. These forecasts will be validated with real-time measurements. Once refined, the model will be tested with satellite data for further validation and scaling up for other stations.

To predict black carbon (BC) concentrations, several models will be used: ARIMA for time-series forecasting, Random Forest and XGBoost for machine learning-based predictions, Fuzzy Logic for handling uncertainty, Support Vector Regression (SVR) for continuous outcomes, and Multilayer

Perceptron (MLP) and Artificial Neural Networks (ANNs) for neural network-based analysis. The best-performing model will be selected for validation and refinement to ensure accurate BC predictions for effective emission mitigation.

3.8.2 Retrieval of Black Carbon from Satellite Imagery:

The Modern-Era Retrospective Analysis for Research and Applications, Version 2 (MERRA-2) provides a valuable dataset for understanding black carbon (BC) dynamics, particularly in regions with limited ground-based measurements. MERRA-2 is a state-of-the-art atmospheric reanalysis project by NASA's Global Modelling and Assimilation Office (GMAO), which integrates satellite observations with climate models to produce global atmospheric datasets. This reanalysis provides data on various atmospheric components, including black carbon, which are critical for comprehensive climate and pollution studies.

This study will use black carbon data from the MERRA-2 Data Portal to analyze its concentration, distribution, and trends in the Indo-Gangetic Basin, particularly in Agra. The high-resolution, gridded BC data is accessible via the NASA Giovanni platform, enabling the download of specific variables like surface concentration across different time intervals.

To access and analyze black carbon (BC) data for the Indo-Gangetic Basin using, the NASA Giovanni Platform will be used. It will start with visiting NASA Giovanni and selecting "MERRA-2" as the data source (Gelaro et al., 2017). The parameters like "Black Carbon Surface Mass Concentration" or "Black Carbon Column Mass Density" will be chosen to get insights into BC levels at the surface and throughout the atmosphere. We will define our study area to include Agra and select the appropriate time period for analysis. We will use Giovanni’s tools to generate visualizations, such as maps and time-series plots, and download the data in formats like NetCDF for further analysis. The satellite data will be cross-referenced with ground-based measurements from the Agra AE-33 Aethalometer to validate and refine our estimates of black carbon (BC) concentrations. This approach will enhance our understandingof BC dynamics and help to develop effective emission reduction strategies.

3.1 Mitigation of Black Carbon

To effectively gather insights on strategies for mitigating Black Carbon (BC) emissions, a structured survey methodology will be implemented as follows:

- **Questionnaire Design**: A detailed questionnaire will be designed and served on the different dynamics (concentration, causes, impacts and solutions) of black carbon (BC), incorporating both quantitative and qualitative questions.
- **Target Respondents**: The questionnaire will be served to academicians, policymakers, experts, researchers, and the general public, ensuring a diverse range of perspectives.
- **Distribution**: The email, social media, and online platforms will be used to maximize the reach to community.
- **Data Collection**: The responses will be gathered over time, with follow-up reminders to encourage participation.
- **Data Analysis**: The data will be analyzed to identify trends, challenges, and barriers related to BC.
- **Reporting**: The findings will be summarized, and evidence-based recommendations will be developed as paradigms to mitigate the menace of black carbon pollution.

3.2 Statistical Analysis

All the datasets will be subjected to statistical analysis. The statistical analysis (viz., mean, standard deviation, variance, correlation, regression, ANOVA, hypothesis testing, Chi-square test, and Pearson/Spearman correlation) of the entire dataset will be performed using statistical tools such as MATLAB, SigmaPlot, SPSS, and Origin. These tools help to analyze data patterns, validate findings, and make conclusions. MATLAB will facilitate custom analysis and advanced modelling, while Sigma Plot willprovide precise graphical representations and detailed statistical analysis. SPSS will be used for hypothesis testing, correlation, and regression analysis to examine relationships between variables, and Origin will aid in data interpretation and fitting. Collectively, these statistical methods will help uncover data patterns, validate findings, and draw meaningful conclusions.

Expected Outcome

The present study will come out with several notable outcomes:

- Detailed analysis of black carbon (BC) concentration patterns in Agra will provide insights into daily, weekly, and seasonal variations.
- Precise quantification of the proportion of modern (biomass) versus fossil carbon in urban

pollution, combined with improved accuracy in source apportionment, models through AI-based validation and refinement, will facilitate more effective targetedmitigation strategies.

- Comprehensive data on the seasonal variation of dry deposition flux of BC will enhance our understanding of its impact on underlying surfaces, particularly in relation to vegetation and soil in local and regional environments and derive critical load.
- Detailed data of BC fosters the calculation of BC's radiative forcing, contributing to the understanding of its climatic effects and enhancing the accuracy for prediction and climate change model.
- Capacity building to scale data predictions across larger geographical areas, improving overall air quality monitoring coverage.
- Analysis of long-term black carbon datasets and a developed predictive model may be useful for policymakers, government bodies, non-governmental organizations (NGOs), industrialists, and academicians to plan mitigation strategies and set standards for black carbon concentration.
- The survey-based developed paradigms for mitigation of black carbon at Agra will be like pilot work and will come out as a boon to encourage reduction of black carbon emissions.

Implications

This study provides a comprehensive understanding on the complex nature of black carbon, offering valuable insights to academicians, researchers, NGOs, government bodies, and policymakers.

- Comprehensive data on BC dynamics informs policymakers in developing evidence-based air quality regulations, enabling tailored policies to reduce BC emissions and contribute to world sustainable development goals (SDGs).
- Detailed understanding of BC pollution exposure and prediction helps safeguard public health, while increased public awareness on air pollution issues which can drive community engagement, support for environmental initiatives, and develop climate resilient societies.
- Holistic approach combining ground measurements, AI/ML models, and satellite observations guides comprehensive policy development at low cost.
- Enables informed decision-makers for effective environmental management and public health

protection.

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